MARGIN CHANGES AND FUTURES TRADING ACTIVITY: A NEW APPROACH

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Abstract

In this paper we examine the impact of margins, adjusted for underlying price risk proxied by market volatility, on trading volume and incorporate the relationship between trading volume and price volatility documented in stock markets. We estimate a bivariate GARCH-M model to take account of the inter-relationships and apply them to the Greek derivatives market over the period 1999-2005. The results show that when adjusting margins for market risk there is no impact on trading volume, casting doubts on the results of previous research, and providing support for the view that margin requirements are used only as a mechanism to prevent trader default.

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1. Introduction

In futures contracts traders are not required to put up the entire value of a contract but to post a margin that is typically between 2% and 10%. Unlike stock margins, margins in the futures markets are not down payments, but are performance bonds that are designed to ensure that traders can meet their financial obligations. A substantial amount of research on margin requirements has been on the relationship between margin requirements and trading volume. The empirical evidence however has generally failed to document a strong inverse association as theory suggests. According to Dutt and Wein (2003) the reason for that is because previous research has failed to consider empirically, although having discussed the rationale for it, that exchange margin committees change margins when they believe that market risk has changed. [1] For example, if price volatility increases, the exchange margin committee will raise margins in response to the increase in market risk[2] and that will have a negative impact on volume since margins are a cost to the trader.[3] However, the increase in price volatility is correlated with trading volume at the same time (see e.g. Jacobs & Onochie, 1998). Since the two effects on volume are of opposite sign, the predicted impact of a margin increase will be ambiguous.

The aim of this study is to provide further empirical evidence on the effects of margin changes on trading volume.

The main contributions of the paper to the literature are: First it adjusts margins for underlying price risk proxied by market volatility as suggested by Dutt and Wein (2003); and second, at the same time it incorporates the relationship between trading volume and price volatility, which is widely documented in equities and futures markets.

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[1] See e.g. and Fishe and Goldberg (1986).
[2] See e.g., and Chatrath, Adrangi and Allender (2001).

Third, the study is novel in that it employs a new econometric methodology to allow for these inter-relationships, which was not considered in previous empirical research. It estimates bivariate GARCH-M models,[4] which allow for autocorrelation in the first and second moments, for nonlinearities in the second moments, provide a means for estimating a risk premium and have the advantages of avoiding simultaneity bias with regard to the relationship between volume and price volatility.

The tests are also conducted on the stock index futures of the Greek derivatives market, a newly established market, which has been rapidly expanding to match that of its European counterparts during a time when the Greek economy and financial markets were experiencing important developments and undergoing significant changes.[5] This issue has never been examined before in the context of the Greek derivatives market. In particular, the study conducts the tests on a large-capitalisation index futures contract (i.e. FTSE/ASE 20 Index) comprising of the 20 largest stocks in terms of market capitalisation and liquidity. Previous studies, such as Chatrath, Adrangi and Allender (2001), and Dutt and Wein (2003), have primarily focused on individual financial and/or commodity futures contracts.

In summary, our investigation has the following main objectives: (i) to examine whether changes in margin requirements have significantly affected trading volume; (ii)

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[3] See e.g. Hartzmark (1986), and Fishe, Goldberg, Gosnell and Sinha (1990).

[4] See Bauwens, Laurent and Rombouts (2006) for a recent survey on multivariate GARCH (MGARCH) models. They assert that these models are important for the study of the relations between the volatilities and co-volatilities of several assets and markets, since it is now widely accepted that financial volatilities move together over time across assets and markets.

[5] These important developments and changes include, among others, the official entry of Greece into the European Economic and Monetary Union (EMU) on January 1, 2001, and the official upgrade of Greek financial markets by Morgan Stanley Capital International (MSCI) from an emerging to developed status on June 1, 2001.

to investigate the effects of margin changes on trading volume, after adjusting margins for underlying price risk, and (iii) to incorporate in the analysis of the effects of margin changes on trading volume the empirical regularity of a positive contemporaneous correlation between trading volume and price volatility.

The remainder of the paper is organised as follows. Section 2 reviews the literature on the effects of margin requirements on trading volume in the futures markets, and the relationship between trading volume and price volatility. Section 3 provides a brief discussion of the establishment and development of the Greek derivatives market. Section 4 describes the univariate and bivariate GARCH-M models, which are employed to examine the effects of margin changes on trading volume. This section also sets up the hypotheses to be tested. Section 5 describes the data and presents the empirical results. The final section summarises the empirical findings and presents the main policy conclusions.

2. Literature review

Previous literature has found little evidence of an inverse association between margins and volume although it has documented a small inverse relationship with respect to open interest. Fishe and Goldberg (1986) examined the effect of margin changes on both open interest and volume around a 3- to 5-day window of such changes of futures contracts trading on the CBOT, like corn, iced broilers, wheat, gold, silver, oats, plywood, soybean meal, soybean oil, and soybean over the period 1972 to 1978. They found, on the one hand, increases in margin requirements would reduce open interest, and on the other hand, they found that increases in margins would increase volume traded.

This finding was explained by the fact that as margin requirements increase, volume increases as well, as traders move to unwind their futures positions in order to avoid the higher costs imposed, eventually causing a net reduction in open interest.

Other empirical studies have also failed to identify statistically significant inverse relationships between margins and volume. For example, Hartzmark (1986) investigated 13 contract days calculating whether volume changed significantly from 15 days before to 15 days following the change. He found that in only 4 of 13 occurrences did volume move negatively and significantly in the opposite direction. As a result, the association between margins and volume is also weak over the longer period and does not support the assertion that increased margin requirements will reduce trading volume.

More recently Dutt and Wein (2003) when examining 3 financial futures contracts (gold, Dow Jones and 10-year Treasury Notes) and 3 agricultural futures contracts (wheat, corn and oats) over a 17-year time period found statistically positive and/or insignificant relationships between volume and margin changes, as was the case in previous research. However, after adjusting margins for underlying price risk, using variability estimates calculated as the variance of the daily settlement price changes for 20 days before and 20 days after each margin change, they find a statistically significant inverse relationship between margin changes and trading volume in all 6 futures contracts. Furthermore, the effect is more evident in financials than in the more traditional agricultural futures contracts.

Our study draws also from another strand of literature, which examined the relationship between trading volume and volatility. Several studies have documented a positive contemporaneous correlation including the seminal paper by Karpoff (1987), In the Greek context Phylaktis, Kavussanos and Manalis (1996) investigated the relationship between volume and volatility in the Athens Stock Exchange (ASE) in Greece and found a positive conditional volume-volatility relationship, when they applied a GARCH-type volatility specification and introduced lagged volume in the variance equation.

The positive relationship between trading volume and price volatility is also documented in the futures markets. For example, Tauchen and Pitts (1983) found a positive relationship between trading volume and price volatility when examining futures on Treasury bills. Jacobs and Onochie (1998) applied bivariate EGARCH-M modelling and looked at a cross-section of financial futures trading on LIFFE. They found a positive relationship between trading volume and price volatility, as measured by the conditional heteroscedasticity of price change.[6]

In view of this widespread evidence on the relationship between trading volume and volatility, the current study takes it into account in its investigation of the effects of margin requirements adjusted for market volatility on trading activity.

3. The Greek derivatives market

The Athens Derivatives Exchange S.A. (ADEX) and the Athens Derivatives Exchange Clearing House S.A. (ADECH) were established in 1997 when Law 2533 was enacted to provide the necessary legal framework for the establishment of the derivatives

[9] More recent papers examining the relationship between trading volume and volatility include: Wang (2004), who examine the dynamic relationship between volume and volatility and Fleming, Kirby and Ostdiek (2006), who avoid the simultaneity bias between trading volume and volatility by using state-space methods.

market in Greece.[7] Trading operations were officially inaugurated on August 27, 1999 and since then interest to acquire membership to ADEX and ADECH has remained strong. The number of trading members increased from 40 in 2000 to 55 in 2005 and the number of investor accounts from 3,181 to 27,399 over the same period. The range of derivative products traded in ADEX continued to expand and at present ADEX investors are able to choose from a range of liquid, EUR-denominated products, including futures and options on the blue-chip FTSE/ASE 20 and mid-cap FTSE/ASE Mid-40 indices of the ASE.[8]

All futures market participants – buyers and sellers – must deposit money with their brokers in futures margin accounts to guarantee contract obligations. As far as ADECH's daily operation is concerned, the mark-to-market of the futures position, which is known as daily settlement, is done separately from the margining. Specifically, every day, for each clearing account, two numbers are issued by ADECH. One number is the daily settlement amount that can be either positive or negative, depending on the outcome of the mark-to-market of the futures position, whether it results in profit or loss. The other number is the minimum required balance of the margin account, for example a 10% margin of the nominal value of the futures position. It is the responsibility of each futures trader, every day, through the clearing member, to both pay for the daily settlement amount, if this is negative resulting from a loss-making position, and also maintain the minimum balance of a 10% margin of the futures position, on his or her margin account that ADECH requires.

[7] The Athens Stock Exchange (ASE S.A.) and the ADEX S.A. were merged in July 17, 2002 to form a new company, the Athens Exchange S.A. (ATHEX). ADECH continued to operate as a separate company.

The FTSE/ASE 20 Index futures were initially introduced with a 20% margin on August 27, 1999. Subsequently, on January 7, 2000, the margin requirement for the FTSE/ASE 20 Index futures was decreased to 14% by ADECH. ADECH has the right to increase or decrease the margin required for deposit, under extreme market conditions or at any time it deems as appropriate to act. For example, ADECH had increased the margins from 12% to 16% on September 12, 2001, as a result of the terrorist attacks that occurred in the U.S. the day before. Many such changes in the margin requirements have been performed in the past, since the launch of these products. However, since October 7, 2002, when margins had increased from 12% to 15%, there has been a gradual reduction to the margins, with the last decrease taking place on February 5, 2004, from 11% to10%. The margins have remained unchanged ever since.[9]

4. Methodological issues

This section discusses the univariate and bivariate GARCH-M(p,q) models, which are used to examine the effects of margin changes on trading volume, by taking into account, on the one hand, the effect of conditional volatility of stock returns on margin changes, and on the other hand, the relationship between conditional volatility of stock returns and trading volume. The best univariate GARCH-M(p,q) models are initially selected and these are subsequently used to construct the bivariate GARCH-M(p,q) model. This section also sets up the hypotheses to be tested.

[8] Trading volume of FTSE/ASE Mid-40 is insignificant and for this reason we did not perform the tests on this futures contract.

4.1. Univariate GARCH-M(p,q) models

The conditional mean and conditional variance equations describing the univariate GARCH-M(p,q) models of stock index returns and the level of trading volume are specified in the following two subsections.

4.1.1. Conditional mean and variance of stock returns

The conditional mean of stock returns equation is specified below as follows:

$$\Delta f_t = a_{0\text{uni}} + \sum_{i=1}^{p} b_{iuni}\Delta f_{t-i} + \sum_{j=1}^{q} c_{juni}u^f_{t-j} + d_{1\text{uni}}h^f_t + u^f_t, \qquad (1)$$

where $f_t = \ln(F_t)$ is the natural logarithm of the contract's settlement futures price, F_t; $\Delta f_t = f_t - f_{t-1}$ is the price log-relative, Δf_{t-i} are past returns, u^f_{t-j} are MA terms, h^f_t is the conditional variance of Δf_t, and u^f_t are random disturbance terms.

Equation (1) models the futures return as having a deterministic constituent, $a_{0\text{uni}}$ and $d_{1\text{uni}}h^f_t$, and a stochastic constituent, u^f_t, which is conditionally heteroscedastic and correlated with volume. The normal futures return constituent is also modelled as an ARMA(p,q) process to take into account the possible market inefficiencies. $a_{0\text{uni}}$ is the unconditional expected rate of price change, $d_{1\text{uni}}h^f_t$, is the risk premium where h^f_t is the conditional heteroscedasticity of the futures return process. Regarding the sign of the risk premium views are divided. On the one hand, according to the intertemporal capital asset pricing model (see Merton, 1973) rational and risk-averse investors demand higher risk

[9] For more information on the establishment and development of the Greek derivatives market see *ASE Fact Book 2006*. The historical information on margin requirements was provided by the Risk Management Department of ADECH.

premiums to hold assets during the periods when the pay-off from the asset is riskier. On the other hand, Backus and Gregory (1993) models imply a theoretical negative risk-return trade-off. At the empirical level, the results are also mixed. French, Schwert and Stambaugh (1987) find positive and significant trade-offs. With asymmetric GARCH-in-mean models, Nelson (1991) find negative trade-offs. Using a long historical record of nearly two hundred years of data from the US stock market, Lundblad (2007) finds a positive and significant trade-off across a host of conditional volatility specifications. Finally, Smith, Sorensen and Wickens (2008) show that the equity premium varies through time.

The conditional variance of stock returns equation is specified below as follows:

$$h^f_t = \alpha_{0\mathrm{uni}} + \sum_{i=1}^{p} \beta_{iuni} h^f_{t-i} + \sum_{j=1}^{q} \gamma_{juni} u^f_{t-j} + \delta_{1\mathrm{uni}} v_{t-1}, \tag{2}$$

where $\alpha_{0\mathrm{uni}} \geq 0$, and β_{iuni}, $\gamma_{juni} \geq 0$ to ensure $h^f_t > 0$. The sum of the coefficients β_{iuni} and γ_{juni}, denote the degree of persistence in the conditional variance given a shock to the system.

The coefficient, $\delta_{1\mathrm{uni}}$, shows the impact of volume and represents the effect of information flow upon price change through the volatility of return, which is in traders' information sets and, as such, is separate from the contemporaneous correlation of the innovations. Consistent with the MDH and many models of sequential information transmission and noisy rational expectations equilibrium, the coefficient, $\delta_{1\mathrm{uni}}$, is expected to have a positive sign.[10] Therefore, the first hypothesis to be tested is set up as follows:

[10] For an elaboration of the MDH, see e.g. Clark (1973).

$$\text{H1: } \delta_{1\text{uni}} > 0$$

We use lagged volume as an instrument for contemporaneous volume to avoid the problem of simultaneity since lagged values of endogenous variables are classified as predetermined (see e.g. Harvey, 1989).

4.1.2. Conditional mean and variance of trading volume

The conditional mean of trading volume equations are specified below as follows:

$$v_t = e_{0\text{uni}} + \sum_{i=1}^{p} g_{iuni} v_{t-i} + \sum_{j=1}^{q} k_{juni} u^v_{t-j} + l_{1\text{uni}} t + n_{1\text{uni}} h^v_t + w_{1\text{uni}} m_t + \ldots$$
$$\ldots + y_{1\text{uni}} r_t + z_{1\text{uni}} x_t + u^v_t, \tag{3a}$$

$$v_t = e_{0\text{uni}} + \sum_{i=1}^{p} g_{iuni} v_{t-i} + \sum_{j=1}^{q} k_{juni} u^v_{t-j} + l_{1\text{uni}} t + n_{1\text{uni}} h^v_t + w_{2\text{uni}} (m_t / h^f_{t-1}) + \ldots$$
$$\ldots + y_{1\text{uni}} r_t + z_{1\text{uni}} x_t + u^v_t, \tag{3b}$$

where $v_t = \ln(V_t)$ is the natural logarithm of the level of trading volume, V_t; v_{t-i} are past terms, u^v_{t-j} are MA terms, h^v_t is the conditional variance of v_t, and u^v_t are random disturbance terms.

Volume has deterministic and stochastic constituents as well. The normal volume constituent is modelled as an ARMA(p,q) process with the margin level, m_t, either unadjusted [see equation (3a)], or adjusted for underlying price risk, denoted by h^f_{t-1} [see equation (3b)], a short-term interest rate, r_t, time to contract maturity, x_t, and a time-trend variable, t.

The innovation, u^v_t, is interpreted as abnormal volume. We include lagged terms to accommodate possible persistence in abnormal volume following an information event as noted in several asymmetric information models of trading volume (see Karpoff, 1986). The use of the conditional volatility (h_t^v) in volume allows one to separate increases in volume due to informed market participants from the uninformed traders as well as from surprises. If the arrival of new information is associated with increased asymmetry of information among traders and an increase in trading volume and is proxied by h^v_t, the estimated coefficient, $n_{1\mathrm{uni}}$, is expected to be positive.

The margin level, m_t, on day t, is included to examine the effects of margin requirements on trading volume. As explained in Section 1 if m_t is not adjusted for market risk proxied by market volatility, its impact on trading activity will be ambiguous. This is so because increases in market volatility cause an increase in margins, which are a cost to the trader and consequently reduce volume. At the same time, the increases in volatility might lead to increases in volume traded as is empirically documented in the literature for the futures markets.

In equation (3b) we follow Dutt and Wein (2003) and adjust margins to expected changes in market risk. Dutt and Wein (2003) used the variance of the daily settlement price changes for 20 days before and 20 days after, for each margin change as a proxy for risk. In our study margins are adjusted for market risk, using the lagged conditional variance of the change in daily settlement prices, denoted by h^f_{t-1}. According to Dutt and Wein's (2003), Fishe end Goldberg's (1986), interpretations, it is changes in margins at given levels of risk that would inversely affect volume. Based on this rationale, the coefficient, $w_{2\mathrm{uni}}$, in equation (3b), which examines the effects of margins, when adjusted, on trading volume, is predicted to be negative. Thus, our second hypothesis is set up as follows:

$$\text{H2: } w_{2\mathrm{uni}} < 0$$

A short-term interest rate, the Euro Overnight Index Average (EONIA) rate, r_t, is included to represent the short-term changes in storage and holding costs and may therefore affect volume.[11] The coefficient, $y_{1\text{uni}}$, is expected to have a negative sign, since an increase in the cost of holding inventories would lead to a reduction in futures market activity.

Time to contract maturity, x_t, that is, the number of days until expiration of the contract on day t, affects contract volume and is therefore included in the model. The coefficient, $z_{1\text{uni}}$, is expected to have a positive sign, that is, as the contract approaches its expiry trading volume increases as futures traders begin to close out their positions to avoid receiving the physical commodity and at the same time open new positions in other contracts with longer expiry dates.

Finally, a time-trend variable, t, is included to control for long-term changes in contract interest.

The conditional variance of trading volume equation is specified below as follows:

$$h^v{}_t = \varepsilon_{0\text{uni}} + \sum_{i=1}^{p} \zeta_{iuni} h^v{}_{t-i} + \sum_{j=1}^{q} \eta_{juni} u^v{}_{t-j} + \theta_{1\text{uni}} \Delta f_{t-1}, \tag{4}$$

where $\varepsilon_{0\text{uni}} \geq 0$, and ζ_{iuni}, $\eta_{juni} \geq 0$ to ensure $h^v{}_t > 0$.

The coefficient, $\theta_{1\text{uni}}$, the lagged return in the conditional variance of volume models the informational impact of price on volume. To the extent that price increases

[11] EONIA is the effective overnight reference rate for the euro. It is computed as a weighted average of all overnight unsecured lending transactions undertaken in the interbank market, initiated within the euro area by the contributing banks. EONIA is computed with the help of the European Central Bank (ECB). The historical data of EONIA was provided by Reuters Support Services.

signal lower systematic risk, so that there is less hedging and/or speculative activity relative to informationally motivated trade, the expectation is that the coefficient estimate of $\theta_{1\text{uni}}$ will be positive. The third testable hypothesis is therefore set up as follows:

$$H3: \theta_{1\text{uni}} > 0$$

4.2. Bivariate GARCH-M(p,q) model

This section discusses the bivariate GARCH-M(p,q) model, which is constructed using the best selected univariate GARCH-M(p,q) models. The conditional mean, the conditional variance and conditional covariance equations describing the bivariate GARCH-M(p,q) model are specified below as follows:[12]

$$\Delta f_t = a_{0\text{biv}} + \sum_{i=1}^{p} b_{ibiv}\Delta f_{t-i} + \sum_{j=1}^{q} c_{jbiv}u^f_{t-j} + d_{1\text{biv}}h^f_t + u^f_t, \tag{5}$$

$$v_t = e_{0\text{biv}} + \sum_{i=1}^{p} g_{ibiv}v_{t-i} + \sum_{j=1}^{q} k_{jbiv}u^v_{t-j} + l_{1\text{biv}}t + n_{1\text{biv}}h^v_t + w_{1\text{biv}}m_t + \ldots$$
$$\ldots + y_{1\text{biv}}r_t + z_{1\text{biv}}x_t + u^v_t, \tag{6a}$$

$$v_t = e_{0\text{biv}} + \sum_{i=1}^{p} g_{ibiv}v_{t-i} + \sum_{j=1}^{q} k_{jbiv}u^v_{t-j} + l_{1\text{biv}}t + n_{1\text{biv}}h^v_t + w_{2\text{biv}}(m_t/h^f_{t-1}) + \ldots$$
$$\ldots + y_{1\text{biv}}r_t + z_{1\text{biv}}x_t + u^v_t, \tag{6b}$$

$$(u^f_t, u^v_t)^T \sim N((0,0)^T, H_t), \tag{7}$$

[12] The diagonal VECH formulation, of Bollerslev, Engle and Wooldridge (1988), is employed for the construction of the bivariate GARCH-M(p,q) model, to allow for greater flexibility and the inclusion of the various exogenous variables in the conditional mean, variance and covariance equations. The diagonal VECH formulation was preferred to the BEKK formulation of Engle and Kroner (1995), since the BEKK model is more complex and consequently more difficult to construct (see Brooks, 2002). Jacobs and Onochie (1998) also use a diagonal VECH formulation for the estimation of a bivariate EGARCH-M(p,q) model, to examine the relationship between return variability and trading volume in international futures markets.

$$(h^f{}_t, h^{fv}{}_t, h^v{}_t)^T = \text{vech}(H_t), \tag{8}$$

$$h^f{}_t = \alpha_{0\text{biv}} + \sum_{i=1}^{p} \beta_{ibiv} h^f{}_{t-i} + \sum_{j=1}^{q} \gamma_{jbiv} u^f{}_{t-j} + \delta_{1\text{biv}} v_{t-1}, \tag{9a}$$

$$h^v{}_t = \varepsilon_{0\text{biv}} + \sum_{i=1}^{p} \zeta_{ibiv} h^v{}_{t-i} + \sum_{j=1}^{q} \eta_{jbiv} u^v{}_{t-j} + \theta_{1\text{biv}} \Delta f_{t-1}, \tag{9b}$$

$$h^{fv}{}_t = \iota_{0\text{biv}} + \sum_{i=1}^{p} \kappa_{ibiv} h^{fv}{}_{t-i} + \sum_{j=1}^{q} \lambda_{jbiv} u^{fv}{}_{t-j} + \mu_{1\text{biv}} \sqrt{|\Delta f_{t-1} v_{t-1}|}, \tag{9c}$$

$$L(\theta|Y,u) = -1/2 \sum_{t=0}^{T} (\ln (2\pi) + \ln|H_t| + u^T{}_t H_t{}^{-1} u_t). \tag{10}$$

As previously stated, $f_t = \ln(F_t)$ is the natural logarithm of the contract's settlement futures price, F_t; $\Delta f_t = f_t - f_{t-1}$ is the price log-relative; $v_t = \ln(V_t)$ is the natural logarithm of the level of trading volume, V_t; and $u_t = (u^f{}_t, u^v{}_t)^T$ is the vector of random disturbance terms for log-relative price and log volume at time, t, respectively, with zero mean vector, 0, and conditional variance-covariance matrix, H_t, with elements, vech(H_t) = $(h^f{}_t, h^{fv}{}_t, h^v{}_t)^T$, as the respective conditional variances and covariance. Y,u are time series of observations and disturbances, respectively, and $L(.|.)$ is the log-likelihood of the parameter vector, θ, conditional on the observations.

Equations (5-6b) describe a bivariate GARCH-M(p,q) structure for the first moments, similar to the univariate GARCH-M(p,q) models presented in the previous subsections. Equations (9a-c) describe a bivariate GARCH-M(p,q) structure for the second moments. The cross-equation structure restricts the conditional moments to depend only upon their past levels, mean equation innovations, and lagged levels of the other variable.[13] Equations (9a-b) are similar to the univariate GARCH-M(p,q) models as previously presented.

The contemporaneous correlation between price change and volume is measured by the coefficient, $\iota_{0\text{biv}}$, in the conditional covariance equation, that is, equation (9c). The MDH, several sequential information, and noisy rational expectations models suggest that this coefficient should be positive. The majority of both the empirical and theoretical literature also documents a positive correlation. Based on this, the fourth testable hypothesis is set up as follows:

$$\text{H4: } \iota_{0\text{biv}} > 0$$

We estimate the models using an iterative procedure based upon the method of Broyden, Fletcher, Goldfarb and Shanno (BFGS) to maximise the log-likelihood function. The quasi-maximum likelihood procedure of Bollerslev and Wooldridge (1992) is also applied, in order to estimate robust standard errors and covariance.

5. Empirical analysis

5.1. Data

The data set comprises daily observations of settlement prices and trading volume, that is, the number of contracts traded, for the nearby futures contract of the FTSE/ASE 20 Index, from August 27, 1999 to December 31, 2005, giving us in total 1,584 observations. The data is collected from the ADEX records. The FTSE/ASE 20 Index comprises of the 20 largest in market capitalisation and most highly traded stocks of all the companies listed on the ASE. It represents over 50% of ASE's total

[13] Including contemporaneous variables results in difficulty of interpretation, more complex asymptotics and less tractable estimation (see Hamilton, 1994).

capitalisation and currently has a heavier weight on banking, telecommunication and energy stocks.

Table 1 reports descriptive statistics of the daily stock index returns and trading volume. As it can be seen the returns series is positively skewed and highly leptokurtic compared to the normal distribution. It also displays significant first order autocorrelation. The Ljung-Box (1978) Q(20) statistic for 20th order autocorrelations is statistically significant, while the Ljung-Box test statistic $Q^2(20)$ (for the squared data) indicates the presence of conditional heteroskedasticity.

The volume series is negatively skewed and leptokurtic compared to the normal distribution. It displays significant autocorrelations, which remain large for the ten lags reported. Significant autocorrelations in trading activity series have also been found in many earlier studies including Phylaktis and Kavussanos (2001) in their investigation of the volatility-volume relationship in the Greek capital market. The Ljung-Box (1978) Q(20) statistic for 20th order autocorrelations is statistically significant, while the Ljung-Box test statistic $Q^2(20)$ (for the squared data) indicates the presence of conditional heteroskedasticity. The Augmented Dickey-Fuller (ADF) test statistic for unit roots indicates that the trading volume series is I(0).

The empirical results of the univariate and bivariate GARCH-M(p,q) models for the FTSE/ASE 20 Index nearby futures contract from August 27, 1999 to December 31, 2005, are presented in the next subsections.

5.2. Estimates of univariate GARCH-M(p,q) models

The following two subsections present the maximum likelihood estimates of the univariate GARCH-M(p,q) models for stock index returns and trading volume. The results of different univariate GARCH-M(p,q) models of stock index returns are reported in Table 2, while those of trading volume are reported in Tables 3 and 4. Each table has three panels. Panel A presents the estimates of the conditional mean equation, Panel B presents the estimates of the conditional variance equation, and Panel C presents the model diagnostics.

The appropriate univariate GARCH-M(p,q)-ARMA(p,q) models are selected using mainly the Akaike (AIC) and Schwarz (SIC) information criteria, but also taking into account the significance of the coefficients, the Ljung-Box test statistics Q(20) and $Q^2(20)$, and the sum of the coefficients of lagged squared returns and lagged conditional variances. Moreover, if our modelling is correctly specified, the value of the coefficients of skewness and kurtosis of the standardised residuals should be smaller than the value of skewness and kurtosis of the returns series and volume series respectively.

5.2.1. Results of conditional mean and variance of stock returns

Table 2 reports the estimated results of different univariate GARCH-M(p,q) models of stock index returns. In Panel A of Table 2, the results for the conditional mean of stock index returns are presented, modelled with various ARMA processes. The coefficient estimate of $d_{1\text{uni}}$, which measures the sensitivity of price change to time variation in the risk premium, is negative but statistically insignificant in all four models.

Panel B of Table 2 presents the results for the conditional variance of returns. The sum of coefficients β_{iuni} and γ_{juni}, the past conditional variances and past squared returns respectively, is close to unity, indicating high persistence of volatility over time. The coefficient, δ_{1uni}, the lagged volume in the conditional variance of returns, is negative and statistically significant at the 5% level in models 1 and 4, and significant at the 10% level in models 2 and 3.[14] This is contrary to our predictions of a positive coefficient, and inconsistent with the MDH and several models of sequential information transmission and noisy rational expectations equilibrium. Therefore, the first hypothesis tested, H1, is rejected. Jacobs and Onochie (1998) find positive and significant coefficients in all 6 futures contracts examined.

Panel C of Table 2 contains the model diagnostics. The Ljung-Box statistics Q(20) and $Q^2(20)$ of the standardised and squared standardised residuals respectively exhibit no serial correlation, in all four models, implying that the models are well specified. Moreover, the coefficients of skewness (m_3) and kurtosis (m_4) of the standardised residuals exhibit a smaller value, than the skewness and kurtosis of the returns series respectively, further implying that the models are correctly specified.

Based primarily on the AIC and SIC information criteria, but also taking into account all the other conditions described above, model 1, the GARCH-M(1,1)-ARMA(1,0) model was considered as the most appropriate model.[15] This univariate model is subsequently used to construct the bivariate GARCH-M(p,q) model.

Before we proceed to the results of the conditional mean and variance of trading volume, it is worth noting, that we also attempted an EGARCH-M specification to capture possible asymmetric shocks to volatility (see Nelson, 1991). The estimated

[14] It is worth noting that the coefficient, δ_{1biv}, although it remains negative, it is statistically insignificant in the bivariate GARCH-M(p,q) model.

results of different univariate EGARCH-M(p,q) models of stock index returns for the period August 27, 1999 to December 31, 2005, are reported in Table A of the Appendix.

The first three models in Table A (models 1-3) demonstrate that the conditional variance equation is not well specified, as the Ljung-Box statistic $Q^2(20)$ of the squared standardised residuals exhibits serial correlation. By adding an extra GARCH term in the conditional variance equation, it rectifies this misspecification. Consequently, as shown in model 4, the EGARCH-M(2,1)-ARMA(1,0) model, the conditional variance equation becomes well specified, as the Ljung-Box statistic $Q^2(20)$ exhibits no serial correlation.

Although the leverage effect coefficient, ξ_{1uni}, is found to be negative and statistically significant at the 5% level, indicating the existence of an asymmetric effect in returns, model 4, the EGARCH-M(2,1)-ARMA(1,0) model, is not superior to the GARCH-M(1,1)-ARMA(1,0) model, using the AIC and SIC information criteria. In addition, the estimation of trading volume using the univariate EGARCH-M specification failed to converge, and as a result we could not employ an EGARCH-M specification for the bivariate model.

5.2.2. Results of conditional mean and variance of trading volume

Table 3 reports the results of different univariate GARCH-M(p,q) models of trading volume. The first three models in Table 3 (models 1-3) demonstrate that the conditional mean equation is not well specified, as the Ljung-Box statistic Q(20) of the standardised residuals exhibits serial correlation. By adding more ARMA terms in the conditional mean equation, which are found to be statistically significant, it rectifies this

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[15] The GARCH-M(1,1)-ARMA(1,0) model, is considered superior to model 4, the GARCH-M(2,1)-ARMA(1,0) model, as depicted by the smaller AIC and SIC information

misspecification and the GARCH-M(1,1)-ARMA(3,2) model, i.e. model 4, is now well specified.

We were able to further improve on model 4 by adding an extra MA term and including only one AR term in the conditional mean equation, as depicted by the smaller AIC and SIC information criteria. Therefore model 5, the GARCH-M(1,1)-ARMA(1,3) model was considered as the most appropriate model. This univariate model is subsequently used to construct the bivariate GARCH-M(p,q) model.

Panel A of Table 3 presents the results for the conditional mean of trading volume. In model 5, the selected model, the coefficient, $n_{1\text{uni}}$, of the conditional variance, h^v_t, is found to be positive and statistically significant at the 10% level confirming Jacobs and Onochie's (1998) results. The coefficient, $w_{1\text{uni}}$, which examines the effects of margin requirements on trading volume, is negative and statistically significant at the 5% level. As discussed in the methodological issues section, the coefficient, $w_{1\text{uni}}$, can be either positive, negative, or zero. For example, Fishe and Goldberg (1986) find that a 10% increase in margins would increase volume traded by 14.62%, using a 3- to 5-day window around margin changes. On the other hand, Hartzmark (1986) find that in only 4 of 13 contract days did volume move negatively and significantly in the opposite direction, using a 15-day window around margin changes. Dutt and Wein (2003) find statistically positive and/or insignificant relationships between volume and margins, using a 20-day window around margin changes.

The coefficient, $y_{1\text{uni}}$, the EONIA rate, r_t, is found to be negative but statistically insignificant, failing to support the view that an increase in the cost of holding inventories would lead to a reduction in futures market activity. This result might reflect the

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criteria and the statistically insignificant $\beta_{2\text{uni}}$ coefficient.

relatively low interest rates that prevailed in the Eurozone during the sample period. Looking at the results of earlier studies Dutt and Wein (2003) find negative and statistically significant coefficients in 5 of 6 futures contracts, while Fishe and Goldberg (1986) find positive but insignificant values.

The coefficient, $z_{1\text{uni}}$, time to contract maturity, x_t, is found to be positive and statistically significant. This finding supports the view that as the contract approaches its delivery futures traders begin to close out their positions to avoid receiving the physical commodity and at the same time they open new positions in other contracts with longer expiry dates, consequently causing an increase in trading volume. This is a stronger result when compared with Dutt and Wein (2003), who find mixed results, and Fishe and Goldberg (1986) who find positive and significant values only for the distant futures contract.

Finally, a time-trend variable, t, included to control for long-term changes in contract interest is found to be statistically insignificant.

Panel B of Table 3 presents the results for the conditional variance of volume. The sum of coefficients ζ_{iuni} and η_{juni}, the past conditional variances and past squared returns respectively, is less than 1, and therefore has a stationary variance.

The coefficient, $\theta_{1\text{uni}}$, the lagged return in the conditional variance of volume, is negative, contrary to our expectations of a positive coefficient, but it is statistically insignificant. The lagged return models the informational impact of price on volume, and to the extent that price increases signal lower systematic risk, there is less hedging and/or speculative activity relative to informationally motivated trade. Therefore, the third hypothesis tested, H3, is rejected. This result is in contrast to Jacobs and Onochie (1998), who find positive and significant coefficients in all futures contracts examined.

Panel C of Table 3 contains the model diagnostics, which confirm that the conditional mean and variance equations of volume are well specified.

The same procedure was followed as above, for the selection of the most appropriate model, when margin requirements are adjusted for underlying price risk, using the lagged conditional variance of the change in daily settlement prices, denoted as h^{f}_{t-1}, in the conditional mean equation of trading volume. Table 4 reports the estimated results of different univariate GARCH-M(p,q) models of trading volume.

Models 1 and 2 in Table 4 demonstrate that the conditional mean equation is not well specified, as the Ljung-Box statistic Q(20) of the standardised residuals exhibits serial correlation. By adding more ARMA terms in the conditional mean equation, which are found to be statistically significant, it rectifies this misspecification. Consequently, as it is shown in models 3 and 4, the conditional mean equation becomes well specified, as the Ljung-Box statistic Q(20) exhibits no serial correlation.

We were able to further improve on models 3 and 4, and as previously shown, model 5, the GARCH-M(1,1)-ARMA(1,3) model was considered the most appropriate based mainly on the values of the AIC and SIC information criteria, but also taking into consideration all the other conditions. Panel C of Table 4, which contains the model diagnostics, shows that model 5 is well specified. This univariate model is subsequently used to construct the bivariate GARCH-M(p,q) model.

There are few differences regarding the coefficients between model 5, the preferred model in Table 3 where m_t is unadjusted and model 5, the preferred model in

Table 4, where m_t is adjusted. In the latter the coefficient, $n_{1\text{uni}}$, the conditional variance, h^v_t, is positive but statistically insignificant, unlike the significant coefficient found in the unadjusted model. What is of interest however is that the coefficient, $w_{2\text{uni}}$, which examines the effects of margin requirements adjusted for underlying price risk, using the lagged conditional variance of the change in daily settlement prices, denoted by h^f_{t-1}, is positive and statistically insignificant, against the expectations of a negative coefficient. Thus, by adjusting margins for market risk we find them not to have an impact on trading volume. Thus, the second hypothesis tested, H2, is rejected. This is in contrast to the results of Dutt and Wein (2003), who document a statistically significant inverse relationship between margin changes and trading volume for all futures contracts examined.

5.3. Estimates of bivariate GARCH-M(p,q) model

Table 5 reports the estimated results of different versions of the bivariate GARCH-M(1,1) model of stock index returns and trading volume. The bivariate GARCH-M(1,1) model is constructed using the selected univariate models, that is, the GARCH-M(1,1)-ARMA(1,0) model and the GARCH-M(1,1)-ARMA(1,3) model, for the stock index returns and trading volume respectively.

Model 1 in Table 5 examines the effects of margin requirements on trading volume and compares the results to the findings of previous research. Model 2 examines the effects of margin requirements on trading volume, but margins are adjusted for underlying price risk, using the lagged conditional variance of the change in daily settlement prices, denoted by h^f_{t-1}. The results are compared with Dutt and Wein's (2003) findings, who also adjust margins for market risk. Model 3 also examines the effects of margin requirements on trading volume, but margins are adjusted by the conditional variance of the change in daily settlement prices lagged twice, denoted by h^f_{t-2}. This is done to check the robustness of our results. Finally, model 4 repeats model 2 but includes lagged conditional variance of returns separately in the conditional mean of volume, in order to capture the direct effect of volatility on trading volume, which might have been wrongly accounted for when adjusting margin requirements for risk. The results in models 3 and 4, are similar to the results of the initial model 2, providing further evidence on the robustness of the bivariate GARCH-M(1,1) model.[16,17]

In Panel A of model 1, the results for the conditional mean of stock index returns and trading volume are presented. The conditional mean of returns is modelled as an ARMA(1,0) process, and the conditional mean of volume is modelled as an ARMA(1,3) process. The presence of serial correlation is evident, since the ARMA processes modelled, present statistically significant terms.

The coefficient estimate of $d_{1\text{biv}}$, which measures the sensitivity of price change to time variation in the risk premium, is negative but statistically insignificant, as in the univariate model. The coefficient, $n_{1\text{biv}}$, which measures the impact of the arrival of new

[16] The results are also similar for both models 1 and 2, when using contemporaneous trading volume, instead of lagged trading volume, in the conditional variance of stock index returns.

[17] We have also estimated the bivariate GARCH(1,1) models and the results are similar to the bivariate GARCH-M(1,1) models. The results can be made available upon request from the authors. We also performed a Likelihood Ratio test and reject the null hypothesis that the GARCH(1,1) models (constrained models) are more robust than the GARCH-M(1,1) models (unconstrained models). The LR test statistic for models 1 is 18.18, for models 2 is 16.56, for models 3 is 16.29 and for models 4 is 20.49, indicating that the GARCH-M(1,1) models (unconstrained models) are more adequate than the GARCH(1,1) models (constrained models). The LR test statistics are summarised in Table B of the Appendix.

information on trading volume as proxied by the conditional variance, $h^v{}_t$, is found to be positive and statistically significant at the 5% level, while in the univariate model it is significant at the 10% level.

The results on the remaining coefficients, that is, the margin level variable, m_t, the EONIA rate variable, r_t, time to contract maturity variable, x_t, and time-trend variable, t, are similar to the results reported for the univariate model, and therefore we will not repeat the comments. In effect, m_t, the variable of most interest to our examination, is found to be negative and statistically significant at the 5% level, when margins are not adjusted for underlying price risk.

Panel B of model 1 presents the results for the conditional variances of returns and volume and the conditional covariance between returns and volume. The sum of the coefficients of the past conditional variances and past squared returns, for both the conditional variances of returns and volume, is less than 1.

The coefficient, $\delta_{1\text{biv}}$, the lagged volume in the conditional variance of returns, is negative and statistically insignificant, unlike the negative and significant coefficient found in the univariate model, but still inconsistent with our expectations of a positive coefficient. The coefficient, $\theta_{1\text{biv}}$, the lagged return in the conditional variance of volume, is also negative and statistically insignificant, as in the univariate model, but still inconsistent to our predictions of a positive coefficient. Therefore, the two hypotheses tested, H1 and H3, are both rejected.

The coefficient, $i_{0\text{biv}}$, in the conditional covariance, which measures the contemporaneous correlation between price change and volume, is negative and statistically significant at the 5% level, inconsistent with the MDH, several sequential information, and noisy rational expectations models, which suggest that this coefficient should be positive. Therefore, the fourth hypothesis tested, H4, is rejected. This is in contrast to Jacobs and Onochie (1998) and Wang (2004), who find positive and statistically significant coefficients in the various asset classes examined. However, Wang emphasizes that liquidity and the degree of information asymmetry influences the relation between volume and subsequent volatility and finds that it is negative.[18]

The negative relationship found in the Greek market might be due to excessive noise trading compared with informed trading in the futures market. According to Liu (2007), who examined the different roles played by the two components of trading volume, informed trading and liquidity trading, in the volume-volatility relation using a marketwide private information arrival rate based on Easley et al. (1996) model, the informed trading component is the underlying driving force for the positive volume-volatility relation. The lack of substantial informed trading in the Greek capital market is supported by the low proportion of institutional trading. For example, in 2004, the proportion of institutional investors in Greece was 15%, significantly lower compared with other markets, such as the UK market, where the proportion was 51%.[19]

Panel C of model 1 contains the model diagnostics, which confirm that the conditional mean and variance equations of returns and volume and the conditional covariance equation between returns and volume are well specified.

The results of model 2 are similar to the results of model 1 and therefore we will not repeat the comments. As in the univariate model, coefficient, w_{2biv}, which examines

[18] Similar results to ours have also been found in the equities markets in Darrat, Rahman and Zhong (2003), who examined the contemporaneous correlations between volumes and return volatility in all 30 stocks comprising the DJIA, and found positive statistically significant correlations in only 3 stocks and negative correlation in 8 stocks.

the effects of margin requirements on trading volume, after margins are adjusted for underlying price risk, using the lagged conditional variance of returns, denoted as h^f_{t-1}, is found to be positive and statistically insignificant, failing to find an inverse association between margins and volume traded. This is in contrast to Dutt and Wein's (2003) findings who document a statistically significant inverse relationship between margin changes and trading volume. Thus, the second hypothesis tested, H2, is rejected.

In order to check whether it is the modelling structure which gives us the different results from Dutt and Wein (2003), we applied their modelling technique of the variance, and found the following: (i) for the unadjusted model (model 1 in Table 2 of Dutt and Wein, 2003), a positive and marginally insignificant margin variable in line with Dutt and Wein (2003)[20]; (ii) for the adjusted models (models 2-9 in Table 2 of Dutt and Wein, 2003) using robust standard calculations with Newey-West/Bartlett window and 5 lags, a negative and statistically significant margin variable for various windows of calculating the variance.[21] These results support the conclusion that it is the modelling structure, which gives the different results from Dutt and Wein (2003). As we mentioned in earlier sections our modelling structure takes into account not only the relationship between margins adjusted by market volatility and trading volume, but also the well documented simultaneous relationship between market volatility and trading volume.

As mentioned at the beginning of this subsection, the results in model 3, when margins are adjusted by the conditional variance of returns lagged twice, denoted as h^f_{t-2}, are similar to the results of the initial model 2. In model 4, the lagged conditional variance of returns, denoted as h^f_{t-1}, is separately included in the conditional mean of

[19] See Federation of European Securities Exchanges, 2007.
[20] Fishe and Goldberg (1986) find similar results.

volume, in order to capture the differential effect of margin changes on volume. Although the lagged conditional variance of returns coefficient, s_{1biv}, is found to be negative and statistically significant, contrary to the expectations of a positive coefficient (see e.g. Cornell, 1981), the coefficient, w_{2biv}, is found to be negative but still statistically insignificant. The remaining results are similar to those of the initial model 2.

As part of the model specification and in order to further assess the robustness of the findings, we have also estimated the *t*-statistics for the mean standardised residuals ($\sigma_{sr,t}$ and $\sigma_{tv,t}$) and the mean standardised products of residuals ($\sigma_{sr,t}\ \sigma_{sr,t}$, $\sigma_{tv,t}\ \sigma_{tv,t}$ and $\sigma_{sr,t}\ \sigma_{tv,t}$). The *t*-statistics reported in Panel C of Table 5 indicate that the mean standardised residuals are not significantly different from zero and that the mean standardised products of residuals are not significantly different from one. These results satisfy the Bollerslev and Wooldridge (1992) moment conditions, so we can be reasonably confident that the QML estimates are consistent.

6. Summary and main policy conclusions

The effects of margin requirements on financial markets are not only of interest to academics, but are of practical concern to policy makers. Empirical studies carried out so far have not been able to conclusively resolve the debate on the effects of margin requirements on financial markets.

The current study has added two different dimensions to the examination of margin requirements on trading volume, which should make one treat the results of previous studies with caution. On the one hand, previous research, has generally neglected to consider that margin requirements change in response to changes in price

[21] Results can be made available upon request from the authors.

volatility, and on the other hand, they did not take into account the relationship between price volatility and trading volume.

In our analysis, we employ a bivariate GARCH-M(p,q) model, which is constructed using the best selected univariate GARCH-M(p,q) models. We examine the effects of margin changes on trading volume, using the most liquid futures contract traded in the Greek derivatives market, the FTSE/ASE 20 Index nearby futures contract, for the period August 27, 1999 to December 31, 2005.

The empirical results can be summarised as follows: An association between margin changes and trading volume is not found when margins are adjusted for underlying price risk, using the lagged conditional variance of stock returns, and against the expectations of a negative relationship. This association remains also statistically insignificant, when margins are adjusted by the conditional variance of stock returns lagged twice, and when separately incorporating the lagged conditional variance of stock returns in the conditional mean of trading volume. This highlights the importance of adjusting margin requirements for risk and casts doubts on the results of previous studies which did not allow for these inter-relationships. Regarding the relationship between volatility of stock returns and trading volume, we find a contemporaneous correlation which is negative and statistically significant. As we have explained this could be due to the lack of substantial informed trading in the market.

Finally, it seems that margin requirements are used only as a mechanism to prevent trader default, at least in the case of the Greek derivatives market, and any decisions associated with the changes in margins, had no significant effect on trading volume. The findings further support what Roll (1989) stated in his comprehensive review on the implications for regulatory policy, that there is little evidence in favour of the efficacy of margin requirements, price limits and transaction taxes.

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Table 1
Summary statistics of FTSE/ASE 20 index nearby futures contract (27/08/1999-31/12/2005)

Stock index return is calculated as $\Delta f_t = (f_t - f_{t-1})$ the price log-relative, where $f_t = \ln(F_t)$ is the natural logarithm of the contract's settlement futures price, F_t. Trading volume is calculated as $v_t = \ln(V_t)$, the natural logarithm of trading volume, V_t. ρ_i, where i = 1,…,10 are sample autocorrelations. * denotes significance of diagnostic statistics at the 5% level. Q(20) and $Q^2(20)$ for the squared data, are Ljung-Box statistics of 20th order. ADF(7) is the Augmented Dickey-Fuller test statistic with lag length 7 chosen using SIC; the critical value is -3.413.

	Stock Index Returns	Trading Volume
Mean	-0.000	8.090
Std. Deviation	0.016	1.171
Minimum	-0.106	3.045
Maximum	0.097	10.164
Skewness	0.098	-1.143*
Kurtosis (excess)	4.080*	0.608*
ρ_1	0.080*	0.932*
ρ_2	-0.013	0.905*
ρ_3	-0.016	0.894*
ρ_4	0.041	0.888*
ρ_5	-0.002	0.885*
ρ_6	0.007	0.877*
ρ_7	0.011	0.875*
ρ_8	-0.005	0.877*
ρ_9	-0.014	0.875*
ρ_{10}	-0.022	0.869*
Q(20)	35.41*	24529.93*
$Q^2(20)$	275.78*	23890.28*
ADF(7)		-3.813

Table 2
Univariate GARCH-M(*p*,*q*) estimation of stock index returns
FTSE/ASE 20 index nearby futures contract (27/08/1999-31/12/2005)

For the specification of the univariate GARCH-M(p,q) model refer to equations (1) and (2) below:

$$\Delta f_t = a_{0\text{uni}} + \sum_{i=1}^{p} b_{iuni}\Delta f_{t-i} + \sum_{j=1}^{q} c_{juni}u^f_{t-j} + d_{1\text{uni}}h^f_t + u^f_t, \tag{1}$$

$$h^f_t = \alpha_{0\text{uni}} + \sum_{i=1}^{p} \beta_{iuni}h^f_{t-i} + \sum_{j=1}^{q} \gamma_{juni}u^f_{t-j} + \delta_{1\text{uni}}v_{t-1}. \tag{2}$$

Model 1,is a GARCH-M(1,1)-ARMA(1,0) model, which was considered as the most appropriate model, as depicted by the smaller AIC and SIC information criteria. This univariate model is subsequently used to construct the bivariate GARCH-M(p,q) model. Model 2 is a GARCH-M(1,1)-ARMA(2,0) model, Model 3 is a GARCH-M(1,1)-ARMA(1,1) model and Model 4 is a GARCH-M(2,1)-ARMA(1,0) model.
The subscript *uni* refers to univariate. The figures in parentheses are t-statistics. m_3 and m_4 are coefficients of skewness and kurtosis of the standardised residuals respectively. $X^2(2)$ is the Jarque-Bera-normality test. Q(20) and $Q^2(20)$ are 20th order Ljung-Box statistics of the standardised and squared standardised residuals respectively. AIC and SIC are the Akaike and Schwarz information criteria respectively. * and ** denotes significance at the 5% and 10% level respectively.

Coefficients	Model 1	Model 2	Model 3	Model 4
Panel A. Conditional mean				
$a_{0\text{uni}}$	0.000	0.000	0.000	0.000
	(0.604)	(0.592)	(0.636)	(0.490)
$b_{1\text{uni}}$	0.079*	0.080*	-0.001	0.080*
	(2.861)	(2.660)	(-0.006)	(2.672)
$b_{2\text{uni}}$		-0.009		
		(-0.328)		
$c_{1\text{uni}}$			0.081	
			(0.429)	
$d_{1\text{uni}}$	-0.751	-0.733	-0.910	-0.465
	(-0.334)	(-0.322)	(-0.379)	(-0.203)
Panel B. Conditional variance				
$\alpha_{0\text{uni}}$	0.000*	0.000*	0.000**	0.000*
	(2.084)	(2.032)	(1.801)	(2.165)
$\beta_{1\text{uni}}$	0.856*	0.855*	0.856*	1.111*
	(18.368)	(19.135)	(16.626)	(5.604)
$\beta_{2\text{uni}}$				-0.235
				(-1.227)
$\gamma_{1\text{uni}}$	0.111*	0.111*	0.111*	0.094*
	(3.357)	(3.469)	(3.209)	(3.442)
$\delta_{1\text{uni}}$	0.000*	0.000**	0.000**	0.000*
	(-2.010)	(-1.952)	(-1.751)	(-2.090)
Panel C. Model diagnostics				
m_3	-0.088	-0.093	-0.090	-0.098
m_4	1.519*	1.524*	1.524*	1.536*
$X^2(2)$	154.13*	155.31*	155.41*	158.14*
Q(20)	19.100	19.686	19.481	18.997
$Q^2(20)$	22.633	22.712	22.651	19.963
AIC	-8.2580	-8.2564	-8.2569	-8.2568

SIC	-8.2343	-8.2292	-8.2298	-8.2297

Table 3
Univariate GARCH-M(1,1) estimation of trading volume-Margins unadjusted FTSE/ASE 20 index nearby futures contract (27/08/1999-31/12/2005)

For the specification of the univariate GARCH-M(1,1) model refer to equations (3a) and (4) below:

$$v_t = e_{0\mathrm{uni}} + \sum_{i=1}^{p} g_{iuni} v_{t-i} + \sum_{j=1}^{q} k_{juni} u^{v}_{t-j} + l_{1\mathrm{uni}} t + n_{1\mathrm{uni}} h^{v}_{t} + w_{1\mathrm{uni}} m_t + y_{1\mathrm{uni}} r_t + z_{1\mathrm{uni}} x_t + u^{v}_{t}, \tag{3a}$$

$$h^{v}_{t} = \varepsilon_{0\mathrm{uni}} + \sum_{i=1}^{p} \zeta_{iuni} h^{v}_{t-i} + \sum_{j=1}^{q} \eta_{juni} u^{v}_{t-j} + \theta_{1\mathrm{uni}} \Delta f_{t-1}. \tag{4}$$

Model 5, is a GARCH-M(1,1)-ARMA(1,3) model, which was considered as the most appropriate model, as depicted by the smaller AIC and SIC information criteria. This univariate model is subsequently used to construct the bivariate GARCH-M(p,q) model. Model 1 is a GARCH-M(1,1)-ARMA(1,0) model, Model 2 is the GARCH-M(1,1)-ARMA(2,0) model, Model 3 is a GARCH-M(1,1)-ARMA(1,1) model and Model 4 is a GARCH-M(1,1)-ARMA(3,2) model.
For the rest of thenotes see Table 2.

Coefficients	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A. Conditional mean					
$e_{0\mathrm{uni}}$	1.100*	0.783*	0.009	-0.139*	-0.107
	(3.790)	(3.302)	(0.065)	(-2.584)	(-1.035)
$g_{1\mathrm{uni}}$	0.819*	0.611*	0.975*	0.620*	0.996*
	(50.527)	(22.636)	(83.754)	(45.610)	(458.733)
$g_{2\mathrm{uni}}$		0.252*		0.628*	
		(10.678)		(40.892)	
$g_{3\mathrm{uni}}$				-0.253*	
				(-59.668)	
$k_{1\mathrm{uni}}$			-0.602*	-0.136*	-0.529*
			(-10.046)	(-5.743)	(-20.294)
$k_{2\mathrm{uni}}$				-0.649*	-0.188*
				(-33.227)	(-6.016)
$k_{3\mathrm{uni}}$					-0.085*
					(-3.098)
$l_{1\mathrm{uni}}$	0.000*	0.000*	0.000	0.000	0.000
	(4.660)	(3.261)	(0.621)	(-0.461)	(-0.558)
$n_{1\mathrm{uni}}$	1.812	1.805	1.577*	1.501*	1.217**
	(1.285)	(1.301)	(6.017)	(8.440)	(1.681)
$w_{1\mathrm{uni}}$	-2.271*	-1.890*	-0.683	-0.320*	-0.262*
	(-2.661)	(-3.428)	(-1.494)	(-2.219)	(-2.958)
$y_{1\mathrm{uni}}$	2.387	1.771	0.035	-0.131	-0.194
	(1.167)	(1.045)	(0.037)	(-0.360)	(-0.574)
$z_{1\mathrm{uni}}$	0.003*	0.004*	0.002*	0.001*	0.001*
	(2.460)	(3.625)	(2.696)	(2.322)	(2.209)
Panel B. Conditional variance					
$\varepsilon_{0\mathrm{uni}}$	0.146*	0.124*	0.142*	0.137*	0.112*
	(4.560)	(4.394)	(11.921)	(13.911)	(6.086)
$\zeta_{1\mathrm{uni}}$	0.009	0.102	-0.077	-0.082	0.092
	(0.063)	(0.701)	(-1.105)	(-1.157)	(0.787)
$\eta_{1\mathrm{uni}}$	0.112	0.102	0.105*	0.096*	0.102*
	(1.180)	(1.144)	(10.634)	(16.066)	(3.155)
$\theta_{1\mathrm{uni}}$	-0.524	-0.324	-0.459**	-0.343	-0.338
	(-0.995)	(-0.384)	(-1.702)	(-1.213)	(-1.188)

Panel C. Model diagnostics					
m_3	-0.094	-0.115**	-0.155*	-0.213*	-0.225*
m_4	0.853*	0.944*	0.954*	0.923*	0.929*
$X^2(2)$	50.33*	62.18*	66.42*	68.08*	70.33*
Q(20)	189.678*	114.195*	73.968*	20.744	25.061
$Q^2(20)$	15.569	14.448	18.703	22.544	21.725
AIC	-1.7818	-1.8409	-1.8975	-1.9469	-1.9494
SIC	-1.7445	-1.8002	-1.8568	-1.8960	-1.9018

Table 4
Univariate GARCH-M(1,1) estimation of trading volume-Margins adjusted FTSE/ASE 20 index nearby futures contract (27/08/1999-31/12/2005)

For the specification of the univariate GARCH-M(1,1) model refer to equations (3b) and (4) below:

$$v_t = e_{0\text{uni}} + \sum_{i=1}^{p} g_{iuni} v_{t-i} + \sum_{j=1}^{q} k_{juni} u^v_{t-j} + l_{1\text{uni}} t + n_{1\text{uni}} h^v_t + w_{2\text{uni}}(m_t/h^f_{t-1}) + y_{1\text{uni}} r_t + z_{1\text{uni}} x_t + u^v_t, \quad (3b)$$

$$h^v_t = \varepsilon_{0\text{uni}} + \sum_{i=1}^{p} \zeta_{iuni} h^v_{t-i} + \sum_{j=1}^{q} \eta_{juni} u^v_{t-j} + \theta_{1\text{uni}} \Delta f_{t-1}. \quad (4)$$

Model 5, is a GARCH-M(1,1)-ARMA(1,3) model, which was considered as the most appropriate model, as depicted by the smaller AIC and SIC information criteria. This univariate model is subsequently used to construct the bivariate GARCH-M(p,q) model. Model 1 is a GARCH-M(1,1)-ARMA(1,0) model, Model 2 is a GARCH-M(1,1)-ARMA(2,0) model, Model 3 is a GARCH-M(1,1)-ARMA(4,2) model and Model 4 is aGARCH-M(1,1)-ARMA(4,3) model.
For the rest of the notes see Table 2.

Coefficients	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A. Conditional mean					
$e_{0\text{uni}}$	0.672*	0.378**	-0.206*	-0.239*	-0.159
	(2.372)	(1.723)	(-4.244)	(-4.020)	(-1.108)
$g_{1\text{uni}}$	0.812*	0.615*	0.630*	0.601*	0.999*
	(38.531)	(24.334)	(30.018)	(5.114)	(297.860)
$g_{2\text{uni}}$		0.249*	0.634*	0.159	
		(9.913)	(20.248)	(1.454)	
$g_{3\text{uni}}$			-0.249*	0.426*	
			(-65.188)	(9.530)	
$g_{4\text{uni}}$			-0.016	-0.188*	
			(-0.803)	(-4.735)	
$k_{1\text{uni}}$			-0.155*	-0.129	-0.531*
			(-5.055)	(-1.125)	(-18.728)
$k_{2\text{uni}}$			-0.654*	-0.142*	-0.190*
			(-20.785)	(-2.419)	(-5.672)
$k_{3\text{uni}}$				-0.464*	-0.086*
				(-9.393)	(-2.966)
$l_{1\text{uni}}$	0.001*	0.000*	0.000	0.000	0.000
	(7.243)	(5.816)	(-0.173)	(-0.087)	(-0.065)
$n_{1\text{uni}}$	2.104	1.922	1.357*	1.463*	1.061
	(1.258)	(1.501)	(4.867)	(5.918)	(1.027)
$w_{2\text{uni}}$	0.000*	0.000	0.000	0.000	0.000
	(-2.240)	(-0.867)	(1.442)	(1.074)	(0.918)
$y_{1\text{uni}}$	5.427*	4.183*	0.113	0.243	0.089
	(2.661)	(2.263)	(0.438)	(0.571)	(0.290)
$z_{1\text{uni}}$	0.003*	0.004*	0.001*	0.002*	0.001*
	(2.076)	(3.282)	(2.560)	(2.460)	(2.297)
Panel B. Conditional variance					
$\varepsilon_{0\text{uni}}$	0.159*	0.129*	0.132*	0.130*	0.106*
	(3.139)	(4.228)	(8.078)	(8.067)	(2.681)
$\zeta_{1\text{uni}}$	-0.070	0.076	-0.050	-0.039	0.134
	(-0.280)	(0.463)	(-0.447)	(-0.348)	(0.506)
$\eta_{1\text{uni}}$	0.107	0.101**	0.098*	0.105*	0.104*
	(1.229)	(1.867)	(10.814)	(11.446)	(2.127)

θ_{1uni}	-0.567	-0.355	-0.287	-0.276	-0.279
	(-1.518)	(-0.924)	(-1.092)	(-1.055)	(-0.628)
Panel C. Model diagnostics					
m_3	-0.073	-0.099	-0.216*	-0.212*	-0.224*
m_4	0.758*	0.907*	0.952*	0.980*	0.949*
$X^2(2)$	39.32*	56.80*	72.02*	75.03*	72.71*
Q(20)	183.660*	113.111*	20.506	20.661	25.798
$Q^2(20)$	15.387	13.767	20.731	18.134	19.601
AIC	-1.7790	-1.8370	-1.9476	-1.9443	-1.9471
SIC	-1.7417	-1.7962	-1.8933	-1.8866	-1.8995

Table 5
Bivariate GARCH-M(1,1) estimation of stock index returns and trading volume
FTSE/ASE 20 index nearby futures contract (27/08/1999-31/12/2005)

For the specification of the bivariate GARCH-M(1,1) model refer to equations (5) to (10) below:

$$\Delta f_t = a_{0\text{biv}} + \sum_{i=1}^{p} b_{ibiv}\Delta f_{t-i} + \sum_{j=1}^{q} c_{jbiv}u^f_{t-j} + d_{1\text{biv}}h^f_t + u^f_t, \quad (5)$$

$$v_t = e_{0\text{biv}} + \sum_{i=1}^{p} g_{ibiv}v_{t-i} + \sum_{j=1}^{q} k_{jbiv}u^v_{t-j} + l_{1\text{biv}}t + n_{1\text{biv}}h^v_t + w_{1\text{biv}}m_t + y_{1\text{biv}}r_t + z_{1\text{biv}}x_t + u^v_t, \quad (6a)$$

$$v_t = e_{0\text{biv}} + \sum_{i=1}^{p} g_{ibiv}v_{t-i} + \sum_{j=1}^{q} k_{jbiv}u^v_{t-j} + l_{1\text{biv}}t + n_{1\text{biv}}h^v_t + w_{2\text{biv}}(m_t/h^f_{t-1}) + y_{1\text{biv}}r_t + z_{1\text{biv}}x_t + u^v_t, \quad (6b)$$

$$(u^f_t, u^v_t)^T \sim N((0,0)^T, H_t), \quad (7)$$

$$(h^f_t, h^{fv}_t, h^v_t)^T = \text{vech}(H_t), \quad (8)$$

$$h^f_t = \alpha_{0\text{biv}} + \sum_{i=1}^{p} \beta_{ibiv}h^f_{t-i} + \sum_{j=1}^{q} \gamma_{jbiv}u^f_{t-j} + \delta_{1\text{biv}}v_{t-1}, \quad (9a)$$

$$h^v_t = \varepsilon_{0\text{biv}} + \sum_{i=1}^{p} \zeta_{ibiv}h^v_{t-i} + \sum_{j=1}^{q} \eta_{jbiv}u^v_{t-j} + \theta_{1\text{biv}}\Delta f_{t-1}, \quad (9b)$$

$$h^{fv}_t = \iota_{0\text{biv}} + \sum_{i=1}^{p} \kappa_{ibiv}h^{fv}_{t-i} + \sum_{j=1}^{q} \lambda_{jbiv}u^{fv}_{t-j} + \mu_{1\text{biv}}\sqrt{|\Delta f_{t-1}v_{t-1}|}, \quad (9c)$$

$$L(\theta|Y,u) = -1/2 \sum_{t=0}^{T} (\ln(2\pi) + \ln|H_t| + u^T_tH_t^{-1}u_t). \quad (10)$$

The bivariate GARCH-M(1,1) model is constructed using the selected univariate models, that is, the GARCH-M(1,1)-ARMA(1,0) model and the GARCH-M(1,1)-ARMA(1,3) model, for the stock index returns and trading volume respectively. Model 1 examines the effects of margin requirements on trading volume [equations (5), (6a) and (7)-(10)]. Model 2 examines the effects of margin requirements on trading volume, but margins are adjusted for underlying price risk, using the lagged conditional variance of the change in daily settlement prices, denoted by h^f_{t-1} [equations (5), (6b) and (7)-(10)]. Model 3 also examines the effects of margin requirements on trading volume, but margins are adjusted by the conditional variance of the change in daily settlement prices lagged twice, denoted by h^f_{t-2}. Finally, Model 4 repeats Model 2 but includes the 'lagged' conditional variance of stock index returns separately in the conditional mean of trading volume, denoted as $s_{1\text{biv}}$.
The subscript *biv* refers to bivariate. The figures in parentheses are *t*-statistics. m_3 and m_4 are coefficients of skewness and kurtosis of the standardised residuals respectively. $X^2(2)$ is the Jarque-Bera-normality test. Q(20) and $Q^2(20)$ are 20th order Ljung-Box statistics of the standardised and squared standardised residuals respectively. AIC and SIC are the Akaike and Schwarz information criteria respectively. * and ** denotes significance at the 5% and 10% level respectively. The *t*-statistics for the mean standardised residuals ($\sigma_{\text{sr,t}}$ and $\sigma_{\text{tv,t}}$) and the mean standardised products of residuals ($\sigma_{\text{sr,t}}\,\sigma_{\text{sr,t}}$, $\sigma_{\text{tv,t}}\,\sigma_{\text{tv,t}}$ and $\sigma_{\text{sr,t}}\,\sigma_{\text{tv,t}}$) are also reported. The subscripts *sr* and *tv* in the model diagnostics refer to the stock index returns and trading volume equations respectively.

Coefficients	Model 1	Model 2	Model 3	Model 4
Panel A. Conditional mean				
$a_{0\text{biv}}$	0.000	0.000	0.000	0.001
	(0.706)	(0.744)	(0.732)	(1.215)
$b_{1\text{biv}}$	0.081*	0.083*	0.083*	0.078*
	(3.834)	(2.422)	(2.666)	(3.383)
$d_{1\text{biv}}$	-1.238	-1.135	-1.133	-1.771

	(-0.512)	(-0.510)	(-0.491)	(-1.026)
e_{0biv}	-0.111*	-0.155*	-0.161*	-0.119
	(-35.757)	(-9.168)	(-9.319)	(-1.444)
g_{1biv}	0.996*	0.998*	0.998*	0.996*
	(397.327)	(271.928)	(407.049)	(243.650)
k_{1biv}	-0.527*	-0.528*	-0.528*	-0.533*
	(-29.229)	(-23.219)	(-21.741)	(-20.247)
k_{2biv}	-0.188*	-0.190*	-0.190*	-0.189*
	(-6.631)	(-7.005)	(-6.637)	(-6.715)
k_{3biv}	-0.092*	-0.093*	-0.093*	-0.093*
	(-3.680)	(-3.377)	(-3.674)	(-4.177)
l_{1biv}	0.000	0.000	0.000	0.000
	(-0.499)	(-0.029)	(0.002)	(0.101)
n_{1biv}	1.215*	1.040*	1.081*	1.123*
	(61.982)	(12.509)	(6.492)	(2.049)
s_{1biv}				-44.164*
				(-2.005)
w_{1biv}	-0.242*			
	(-2.692)			
w_{2biv}		0.000	0.000	0.000
		(0.689)	(1.017)	(-0.866)
y_{1biv}	-0.176	0.087	0.092	0.041
	(-0.579)	(0.279)	(0.326)	(0.144)
z_{1biv}	0.001*	0.001*	0.001*	0.001*
	(2.623)	(2.281)	(2.589)	(2.288)
Panel B. Conditional variance and covariance				
α_{0biv}	0.000**	0.000**	0.000**	0.000**
	(1.728)	(1.692)	(1.747)	(1.665)
β_{1biv}	0.854*	0.855*	0.855*	0.867*
	(17.512)	(18.832)	(17.887)	(18.972)
γ_{1biv}	0.110*	0.109*	0.109*	0.102*
	(3.646)	(3.671)	(3.535)	(3.523)
δ_{1biv}	0.000	0.000	0.000	0.000
	(-1.631)	(-1.576)	(-1.636)	(-1.599)
ε_{0biv}	0.108*	0.103*	0.104*	0.103*
	(20.731)	(6.224)	(6.601)	(4.136)
ζ_{1biv}	0.124*	0.163	0.152	0.154
	(7.226)	(1.306)	(1.283)	(0.952)
η_{1biv}	0.094*	0.098*	0.096*	0.101*
	(5.376)	(4.785)	(4.333)	(3.840)
θ_{1biv}	-0.363	-0.316	-0.321	-0.316
	(-1.521)	(-1.332)	(-1.210)	(-1.327)
ι_{0biv}	-0.000*	-0.000*	-0.000*	-0.000*
	(-2.277)	(-2.321)	(-2.797)	(-2.186)
κ_{1biv}	0.849*	0.852*	0.852*	0.847*
	(10.289)	(11.005)	(11.613)	(11.606)
λ_{1biv}	0.041**	0.040	0.040	0.041**
	(1.762)	(1.469)	(1.572)	(1.817)
μ_{1biv}	0.001*	0.001*	0.001*	0.001*
	(2.333)	(2.363)	(2.833)	(2.275)
Panel C. Model diagnostics				
m_{3sr}	-0.080	-0.079	-0.079	-0.078
m_{3tv}	-0.224*	-0.223*	-0.224*	-0.227*
m_{4sr}	1.543*	1.552*	1.552*	1.545*

m_{4tv}	0.924*	0.943*	0.941*	0.889*
$X^2_{sr}(2)$	158.52*	160.45*	160.44*	159.04*
$X^2_{tv}(2)$	69.47*	71.78*	71.52*	65.59*
$Q_{sr}(20)$	18.861	18.780	18.782	18.876
$Q_{tv}(20)$	25.154	25.814	25.845	26.107
$Q^2_{sr}(20)$	22.484	22.863	22.860	23.458
$Q^2_{tv}(20)$	20.481	18.541	18.571	18.961
AIC_{sr}	-8.2552	-8.2552	-8.2552	-8.2516
AIC_{tv}	-1.9508	-1.9484	-1.9487	-1.9521
SIC_{sr}	-8.2314	-8.2315	-8.2315	-8.2277
SIC_{tv}	-1.9033	-1.9009	-1.9012	-1.9013
t-stat. for H_0: $\sigma_{sr,t} = 0$	-0.978	-0.967	-0.973	-0.905
t-stat. for H_0: $\sigma_{tv,t} = 0$	-0.120	-0.180	-0.157	-0.167
t-stat. for H_0: $\sigma_{sr,t}\ \sigma_{sr,t} = 1$	0.039	0.045	0.047	0.158
t-stat. for H_0: $\sigma_{tv,t}\ \sigma_{tv,t} = 1$	-0.018	-0.020	-0.010	-0.066
t-stat. for H_0: $\sigma_{sr,t}\ \sigma_{tv,t} = 1$	1.578	-0.920	-1.404	0.762

Appendix: Table A
Univariate EGARCH-M(p,q) estimation of stock index returns
FTSE/ASE 20 index nearby futures contract (27/08/1999-31/12/2005)

For the specification of the univariate EGARCH-M(p,q) model refer to equations (A) and (B) below. The subscript *uni* refers to univariate. The figures in parentheses are t-statistics. m_3 and m_4 are coefficients of skewness and kurtosis of the standardised residuals respectively. $X^2(2)$ is the Jarque-Bera-normality test. Q(20) and $Q^2(20)$ are 20th order Ljung-Box statistics of the standardised and squared standardised residuals respectively. AIC and SIC are the Akaike and Schwarz information criteria respectively. * and ** denotes significance at the 5% and 10% level respectively.

Model: The conditional mean and variance equations of the univariate EGARCH-M(p,q) specification are:

$$\Delta f_t = a_{0\text{uni}} + \sum_{i=1}^{p} b_{iuni}\Delta f_{t-i} + \sum_{j=1}^{q} c_{juni}u^f_{t-j} + d_{1\text{uni}}h^f_t + u^f_t, \tag{A}$$

$$\ln(h^f_t) = \alpha_{0\text{uni}} + \sum_{i=1}^{p} \beta_{iuni}\ln(h^f_{t-i}) + \sum_{j=1}^{q} \gamma_{juni}|u^f_{t-j}/\sqrt{h^f_{t-j}}| + \sum_{j=1}^{q} \xi_{juni}(u^f_{t-j}/\sqrt{h^f_{t-j}}) + \delta_{1\text{uni}}v_{t-1}, \tag{B}$$

where $f_t = \ln(F_t)$ is the natural logarithm of the contract's settlement futures price, F_t; $\Delta f_t = f_t - f_{t-1}$ is the price log-relative, Δf_{t-i} are past returns, u^f_{t-j} are MA terms, h^f_t is the conditional variance of Δf_t, and u^f_t are random disturbance terms. Unlike the linear GARCH-M(p,q) model there are no restrictions on the parameters $\alpha_{0\text{uni}}$, β_{iuni}, γ_{juni}, and ξ_{juni} to ensure non-negativity of the conditional variance. Persistence of volatility is measured by β_{iuni}. The asymmetric effect of negative and positive shocks is captured by ξ_{juni} and γ_{juni} respectively; ξ_{juni} measures the sign effect and γ_{juni} measures the size effect. If $\xi_{juni} < 0$ a negative shock (bad news) tends to reinforce the size effect. The converse takes place when $\xi_{juni} > 0$. Bad news will mitigate the size effect. Finally, the lagged volume variable, v_{t-1}, is intended to capture the effect of trading volume on the conditional variance of returns.

Coefficients	Model 1	Model 2	Model 3	Model 4
Panel A. Conditional mean				
$a_{0\text{uni}}$	-0.007	-0.006	-0.008	-0.007
	(-1.333)	(-1.157)	(-0.983)	(-1.336)
$b_{1\text{uni}}$	0.065*	0.068*	-0.037	0.065*
	(2.960)	(3.147)	(-0.119)	(2.982)
$b_{2\text{uni}}$		-0.008		
		(-0.315)		
$c_{1\text{uni}}$			0.103	
			(0.339)	
$d_{1\text{uni}}$	-0.001	-0.001	-0.001	-0.001
	(-1.327)	(-1.162)	(-0.995)	(-1.324)
Panel B. Conditional variance				
$\alpha_{0\text{uni}}$	-0.353*	-0.356*	-0.354**	-0.343**
	(-17.109)	(-2.470)	(-1.677)	(-1.772)
$\beta_{1\text{uni}}$	0.966*	0.967*	0.966*	1.102*
	(138.890)	(56.030)	(38.307)	(7.503)
$\beta_{2\text{uni}}$				-0.136
				(-0.878)
$\gamma_{1\text{uni}}$	0.209*	0.210*	0.210*	0.193*
	(6.132)	(3.868)	(2.931)	(2.953)
$\delta_{1\text{uni}}$	-0.011	-0.011	-0.011	-0.011
	(-1.526)	(-1.428)	(-1.335)	(-0.976)
$\xi_{1\text{uni}}$	-0.053*	-0.053*	-0.053*	-0.048*
	(-2.238)	(-2.523)	(-2.344)	(-2.086)

Panel C. Model diagnostics

m_3	0.019	0.015	0.017	0.012
m_4	1.635*	1.639*	1.640*	1.640*
$X^2(2)$	176.35*	177.24*	177.57*	177.33*
Q(20)	21.698	22.067	22.077	21.759
$Q^2(20)$	28.937**	29.236**	28.956**	27.028
AIC	-8.2565	-8.2549	-8.2555	-8.2551
SIC	-8.2294	-8.2244	-8.2250	-8.2246

Appendix: Table B
Test for stability of coefficients

The Likelihood Ratio test statistic is specified as LR = -2 [max Log likelihood (constrained) – (max Log likelihood (unconstrained)]. It follows a chi-squared distribution with d.f. equal to the number of constraints. We assume the same number of AR and MA terms in the two models when estimating the LR test statistic. * denotes significance at the 5% level.

Null Hypothesis	Likelihood Ratio Test
Conditional variance in the mean equation of stock returns and trading volume is equal to zero – Chi-squared (2)	18.18* (Models 1) 16.56* (Models 2) 16.29* (Models 3) 20.49* (Models 4)